Estimating the Costs of Hurricane Evacuation

A Study of Evacuation Behavior and Risk Interpretation using Combined Revealed and Stated Preference Household Data

Kevin Tyndall Smith
Department of Economics
East Carolina University
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I. Introduction

Hurricane evacuation decision-making continues to be a problem for the emergency management community. The ability of emergency managers to accurately and efficiently call for human evacuation orders has recently become a major source of concern and speculation among analysts, households, and the management community themselves. Inaccuracies are due to the uncertainty of storm direction (track), intensity, forward speed, and the time of landfall. Decisions concerning the implementation and timing of evacuation orders (voluntary or mandatory) are based solely on the recommendation of the National Hurricane Center (NHC). The NHC encourages emergency managers to act as though the storm is one level higher (more intense) than it actually is. This has produced an over-warning problem, known as the "Crying Wolf" effect, which many individuals believe reduces the credibility of the emergency managers' decisions. The lack of credibility may lead to a reduction in evacuations and a decrease in household safety if a hurricane does strike. This suggests that the decision to call for an evacuation order should be based not only on the likelihood, timing, and intensity of hurricane conditions and associated storm surge but also on additional knowledge of household behavior that is presently unavailable. The knowledge to be attained should include the likelihood of household evacuation given household location, history, demographics, and responsiveness to evacuation orders at the time of a hurricane threat as well as the costs that are incurred during an evacuation.

In response to problems with disaster management and public response, the NC Division of Emergency Management (DEM) has made aggressive efforts to improve the system. In November of 1998, the DEM contacted East Carolina University to discuss carrying out the following: 1) the creation of a post-Hurricane Bonnie evacuation economic impact analysis report; and 2) a standard hurricane evacuation economic impact methodology for use by the DEM.

The purpose of this paper is to model the decision process of households during a hurricane threat and to predict future household evacuation behavior. I examine the likelihood of household evacuation using data from a survey of North Carolina residents who were affected by Hurricane Bonnie in the summer of 1998. Using revealed preference (RP) and stated preference (SP) data I predict evacuation rates at different levels of storm intensity. RP data refers to the responses of individuals who experienced first-hand the threat of Hurricane Bonnie, and SP data refers to individuals' response to a hypothetical scenario. I use household evacuation costs, and various measures of hurricane risks to test the validity of the RP and SP data. Logistic regression is used to interpret the effect of these variables on the decision of households to evacuate or not.

This paper is organized into six main sections including literature review, theory, data, empirical results, evacuation costs, and conclusions.

The literature review is divided into three parts. One part summarizes the recent history of hurricane evacuation analysis. It is a generalization of many factors that may contribute to the household evacuation decision. The second presents other recent literature on the subject. The third discusses human response to the risk that is incurred during natural disasters.

The theory section lays out the foundation of hurricane evacuation theory, expected utility, and the relationship between a household's evacuation decision and the factors that come into play. The household expected utility function is simplified to include health and income. The main factors that we outline in this section are the effect of income, cost, and probability of good health on evacuation behavior.

The data section introduces the work of Louviere (1996) and Whitehead, Haab, and Huang (1999). They discuss the pros and cons of combining stated preference (SP) and revealed preference (RP) data in predicting future behavior. The methods used to equate the two data sets and the variables used in this analysis are presented in this section.

The empirical section is divided into two main subsections that describe the logistic regression model used in this analysis and presents the empirical results. The empirical results are presented in five further subsections including a comparison between the RP and SP models, an explanation for each of the three combined models considered, and a description of the selection of the probability model used for cost estimation.

The cost estimation section presents the process by which we applied the selected model to the population of the eight NC coastal counties and then estimated costs by hurricane category. The final section presents a concluding explanation of the results from this analysis.

II. Literature Review

The world of hazard preparation is a much evolving field and has only begun to touch on the economic costs of an evacuation. The literature pertaining directly to hurricane evacuation costs is scarce but there is much related research. The literature in this review is pulled from two specific areas of prior research: hurricane evacuation and risk and behavior.

Baker's Literature Review

Baker (1991) reviews empirical studies of hurricane evacuation. He does this through examining household behavior descriptively and assessing possible predictors of household evacuation that researchers have used. These possible predictors include the following variable groups: self-account, risk-level of the area, evacuation notices, housing, storm threat information, experimental data, hurricane experience, length of residence, hurricane awareness, and demographics. He states that household risk assessment is an informative proxy for the household evacuation decision, but it is also a very challenging variable to disclose. Those who do not feel safe staying where they are tend to evacuate, while those who do feel safe tend not to evacuate.

The risk-level of a household's residence can be measured by the elevation above sea level. Residence refers to the structure of the home. This is one of the best predictors of the evacuation decision. This is not surprising since emergency management officials disseminate evacuation orders (MEO and VEO) based on objective household risk measures.

The wording and dissemination of evacuation advice and orders is another important factor in the household decision to evacuate. During Hurricane Frederick (1979), 63% of the residents of Mobile, Alabama evacuated after being advised. Out of those who heard from public officials that they should evacuate, 84% left; of those who didn't hear, only 20% evacuated. Hurricane David (1979) left more profound evidence of this phenomenon in Miami Beach, Florida, where the difference was 88% to 8%.

Whether an individual understands the terminology of hurricane risk information (hurricane watch vs. hurricane warning, voluntary evacuation vs. mandatory evacuation) seems to have little to do with household decisions. See Figure 1 to view the areas that received a hurricane watch and those who received a hurricane warning before Hurricane Bonnie.

Housing is a proxy of risk-level used by both households and emergency managers. For example, mobile home owners are more likely to evacuate than other housing groups and evacuation information may be targeted directly at this group.

Most information-related variables tend to have little or no association with the evacuation decision. Baker cites the following as examples: the households' primary source of news information, the source of initial information about the hurricane, the attention they devoted to monitoring the storm, their confidence in hurricane forecasts, and the recall of forecast information.

No consistent relationship has been documented for whether or not individuals who have had a 'hurricane experience' are more likely to evacuate. More weight might be placed on whether or not an individual has had a 'recent' hurricane experience, or if they have had a 'false alarm'.

Length of residence shows no clear correlation with the evacuation decision for the following reasons: (1) Newcomers may not appreciate the destructive potential of hurricanes and therefore may be less prone to evacuate, and (2) 'false alarms' may result in a negative relationship between length of residence and choosing to evacuate.

The data used to analyze evacuation decision-making has mostly been RP data from hurricanes, but some researchers have used SP data to simulate the response to different hurricane situations. Baker (1991) states that the difficulty in estimating the separate determinants of evacuation behavior is due to high correlation between the variables in the data. This along with an inaccuracy in the “recall” of household behavior, he says, creates a problem in using only RP data. He suggests that SP data with several different scenarios might provide more useful means for examining the separate effects of different variables on public response. Baker (1984) used a hypothetical survey to examine the effects of strike probabilities on individual decision-making. Individuals tend to say they would evacuate in lower risk situations than is actually observed, but responses to higher risk situations resemble closely what has been documented.

Recent Hurricane Evacuation Studies

Peacock and Gladwin (1992) conducted a survey of 1300 households throughout Dade County, Florida, three to four months after Hurricane Andrew. The survey was a SP evaluation used to examine household response in the case of a future hurricane. The critical question asked the respondent to consider the approach of a future hurricane. They gave households the following options: "stay home," "go to safer building," "leave the area entirely," "depends on the strength of the storm," and "don’t know." Almost half (46.9%) of the sample reported that it would depend on the strength of the storm. The remaining respondents were split almost entirely between "stay home" (22.4%), and "leave the area entirely" (21.2%).

They compared their results with a survey that the Institute of Public Opinion Research (IPOR) at Florida International University conducts annually on the entire state of Florida. The IPOR poll was conducted in October, immediately following Hurricane Andrew, while the Dade County survey was conducted in December. Individuals in the

IPOR poll were asked what they would do if a hurricane like Andrew were to strike their area. They were given the same options as individuals in the Dade County survey excluding the "depends on storm severity" option. The IPOR poll produces much higher percentages of individuals who would leave the area. The time of surveying and the nature of the question (dropping the "depends on storm severity" option) may account for some of this difference, as well as the sample the survey is directed towards (entire state of Florida vs. Dade County alone). This again suggests that the severity of the storm should be considered.

Respondents from Peacock's survey who evacuated before Andrew were much more likely to "leave the area" or "go to a safer place" than those who did not. Only households with slight damage from Andrew reported an increase in "leave the area entirely" and a decrease in "depends on the strength of the storm." There is evidence that race also plays a large role in the decision-making process, but it is most likely correlated with income levels. Households with income levels under twenty thousand are more likely to go to a safer place than any other income group, as are Hispanic and black individuals.

Dow and Cutter (1997) attempt to determine the impact of false alarms on the credibility of emergency managers. They performed a survey of residents of Hilton Head and Myrtle Beach, S.C. and Wilmington, N.C. to examine this "Crying Wolf" effect. The survey included three specific questions that individuals were asked to consider. Were there any differences in evacuation responses of residences for Hurricanes Bertha and Fran? Was there an action or a specific piece of information that convinced people to evacuate, and did this vary between the two hurricanes? What was the major source of “reliable” information influencing the decisions to evacuate and did this differ in the two hurricane events?

Of the respondents 39% evacuated for both hurricanes, 37% stayed home for both, 21% did not evacuate for Bertha but evacuated for Fran. Results of the survey suggested that households were making use of the information disseminated by mass media. There was more reliance on the forecast of the storm itself rather than what other households were doing. The role of media coverage in the decision-making process varies, however, with its timing, personal relevance, and credibility. The stronger determinants of evacuation behavior all seem to be tied to personal risk perception. They find a significant reduction in the credibility of government officials from Fran to Bertha, so that they are, in many cases, irrelevant in the households’ decision. Factors such as age, race, gender, and past experience do not show significant differences between evacuees and non-evacuees.

The authors also examined the evacuation decision of respondents in the case of a future hurricane. The largest portion (48%) reported that it would “depend,” referring predominantly to the severity of the storm. The next largest group (21%) reported that they would not evacuate with a future hurricane threat. Of these individuals, only 2% stated that it was because of past “false alarms" and 81% of them did not evacuate in either Bertha or Fran.

This review suggests several generalizations about household behavior during a hurricane threat. Household residence, as a measure of hurricane risk, is one of the best predictors of the evacuation decision. Wording and dissemination of evacuation advice and orders is another important factor in the household decision to evacuate. 'Recent' hurricane experiences and 'false alarms' seem to be factors that affect the credibility of government warnings and evacuation orders. Household evacuation decisions weigh heavily on the severity of the storm. This review suggests that SP data with several different scenarios might provide more useful means for examining the separate effects of different variables on public response. Emergency management officials could use this information to establish a threshold at which households will evacuate as a function of risk-area, storm category, and evacuation order (warning, voluntary, or mandatory). Cost of evacuation should be examined as a possible deterrent that keeps households from evacuating.

Risk and Behavior

Burton, Kates, and White (1993) cite problems with the data that has been used for environmental disaster behavior analysis. They suggest that the quality of the data used to measure risk and behavior has not changed as rapidly as the organizations and programs directed at coping with the widely rising toll of losses, and that the collection of data has been based on poorly defined concepts of economic effects. This is evident in the omission of a household cost variable in almost all of hurricane evacuation behavior research. Most data have been directed towards the information that households receive (governor's orders, media, warnings by public officials) and the effect it has on their decision process. To make a more complete assessment of individual behavior and risk assessment, data should include both risk information and cost variables.

Burton, et. al., (1993) explore individual choice through the process of utility maximization. If individuals choose on the basis of their assessment of all expected outcomes, they are using the expected utility model. Individuals who choose upon the basis of his/her subjective view of those probabilities are using the subjective expected utility model. Those that choose from the courses of action by subjective assessment of utility with goals of less than the maximum incremental returns are using bounded rational methods.

The authors cite Slovic et. al., (1974) who suggest that the individual choice is made by using the following decision process: 1) appraising the probability and magnitude of extreme events, 2) considering the range of possible alternative actions, 3) evaluating the consequences of selected actions, and 4) choosing one or a combination of actions (see Figure 2).

Burton also cites Kunreuther (1974) who states that the decision process does not begin until a threshold of awareness for actual or anticipated loss is reached. In setting this threshold, how much discretion should be left to the individual and how much should be left to emergency managers and the policies that guide them? Will this help in minimizing traffic problems and unnecessary traffic accidents associated with untimely evacuation decisions?

Burton et. al., (1993) state that many choices during hazard threats can be linked to four basic classes of factors: 1) prior experience with hazard is commonly linked with the choice made, 2) wealth of the individuals concerned is usually associated with the extent to which they take risks, 3) personality traits figure into certain choice, and 4) the perceived role of the individual in the social group may also be influential.

The authors cite Heberlein (1971) who suggests that what the individual does is highly correlated to the recognition of his capacity to act and his sense of social responsibility to do so. This theory should be taken into account when observing the timing of evacuation. When individuals evacuate there is a certain level of danger on the roads. This level of danger can be minimized if individuals recognize their social responsibilities to evacuate when they are informed to. This will decrease “bottlenecking,” the crowding of roads used for an evacuation path, and unnecessary traffic accidents, which could be included as a cost of evacuation.

III. Theory

Viscusi (1992) identifies one central finding that is consistent throughout the literature. Individuals assessing the risk of injury/fatality over assess the risks of low-probability and under assess the risks of high-probability events.

Viscusi and O’Connor (1984) experimented with risk perception by comparing subjective risk perception of chemical workers with objective measures of risk in a study involving the labels placed on their chemicals. They estimated perceived risk implied by the introduction of new labels and their relative informational content. The observed coefficients from regression analysis were compared to objective measures of risk in the chemical industry. Subjective risk assessments were higher than the reported injury and illness rates in the chemical industry. These results suggest that individuals can process risk information in the expected direction, but it is the informational content and not the risk level that is instrumental. He suggests the focus should be on whether or not there is risk-related variation in the relative weight placed on new information rather than the level of risk itself. To accomplish this he suggests obtaining the relative emphasis that individuals place on their perceived judgments of risk. I explore the causes of observed biases in risk perception of a hurricane threat by comparing coefficients of objective and subjective risk variables.

The evacuation decision is a function of hurricane intensity, risk-level of the household's residence, demographics, and the probability of a hurricane strike. In order to conceptualize this decision, I employ the Von Neumann-Morgenstern theorem of expected utility (Nicholson, 1998). This theorem is based on the hypothesis that individuals make choices in uncertain situations by maximizing their expected utility. Utility may encompass any number of individual interests including health and financial well-being. Individuals generally dislike uncertain situations and may be willing to pay something to reduce the uncertainty they face.

Consider the following utility function:

$$U = U\ (H, y) \tag{1}$$

where utility (U) is a function of exogenous health status (H) and income (y). Households have two alternative actions given the risk of a hurricane strike, evacuate or stay at home. Households do not have to make choices about a hurricane strike under complete uncertainty. Technology has allowed forecasters to make predictions on a storm's path and the media to disseminate probabilities for whether the hurricane is going to strike a given area. In that case, households are able to make decisions under known probabilities (Burton, 1993). Figure 2 illustrates the evacuation decision process and potential outcomes through a decision tree. The utility functions represent the outcome of both choices with and without a hurricane strike. The letter c represents the cost of an evacuation.

If utility is additively separable in health and income individuals have utility with good health:

$$U(H=1, y) = h(1) + m(y) \tag{2}$$

where H=1 is the case of good health. Good health can be achieved in the absence of a hurricane threat or by avoiding the threat by evacuating. Utility with bad health is

$$U(H=0, y) = h(0) + m(y), \tag{3}$$

where H=0 is bad health. The separability assumption implies that decisions about one good or group of goods do not affect the utility received from some other good or group of goods (Nicholson, 1998).

In the case of a hurricane threat households have a perceived probability of good health (hurricane risk), p and bad health 1-p. With no hurricane threat, households have a perceived probability of good health, q and bad health, 1-q, where $q > p$. Therefore, the expected household utility in the case of a hurricane threat is

$$EU(p) = m(y) + (1-p)h(0) + ph(1), \tag{4}$$

and the expected household utility without a hurricane strike is

$$EU(q) = m(y) + (1-q)h(0) + qh(1). \tag{5}$$

The expected utility gain from avoiding a hurricane threat by evacuation is the difference between (5) and (4) (see Groothius, Van Houtven, and Whitehead, 1988).

$$\Delta EU = m(y-c) + (1-q)h(0) + qh(1) - [m(y) + (1-p)h(0) + ph(1)]$$

$$\Delta EU = m(y-c) - m(y) + (q - p)[h(1) - h(0)] \tag{6}$$

where ΔEU is the change in expected utility and c are the costs of evacuation. Equation (6) can be interpreted as two parts. The first part, $m(y-c) - m(y)$, is the decrease in utility resulting from evacuation costs. The second part, $(q - p)[h(1) - h(0)]$, is the increase in utility resulting from an increase in the probability of good health. If the increase in utility from the increased probability of good health exceeds the decrease in utility from evacuation costs, the household will evacuate. As the ΔEU increases the probability of evacuation will increase.

Comparative static analysis enables us to determine the individual effects of p, y, and c on ΔEU. The effect of the probability of good health in a hurricane threat (p) on ΔEU is:

$$\partial \Delta EU / \partial p = h(0) - h(1) \tag{8}$$

where $h(0) - h(1) < 0$. As probability of good health increases, evacuations are expected to increase.

With respect to income:

$$\partial \Delta EU / \partial y = \partial m(y-c) / \partial y - \partial m(y) / \partial y \tag{9}$$

where $\partial m(y-c)/ \partial y - \partial m(y)/ \partial y > 0$ due to diminishing marginal utility of income. The marginal utility of income with costs of evacuation is greater than the marginal utility of income without costs of evacuation. As income increases evacuations will increase if the marginal utility of income is not constant.

As the costs of evacuation change:

$$\partial \Delta EU / \partial c = \partial m(y-c) / \partial c \tag{10}$$

where $\partial m(y-c)/ \partial c < 0$ because increased costs decrease income which decreases utility. As the cost of evacuation increases, evacuations are expected to decrease. The probability of health without a hurricane strike, q, is assumed to be constant since the probability of good health is the same whether the household evacuates or not.

The probability of good health in the case of a hurricane threat is conditioned on the following function:

$$p = \theta\ (i, r) \tag{11}$$

where i is the set of characteristics that measure hurricane intensity, and r is the set of variables describing the household perceived risk-level and location. Consider the following comparative statics:

$$\partial p/\partial i = \partial\ \theta\ (i,r)\ /\ \partial i \tag{12}$$

and

$$\partial p/\partial r = \partial\ \theta\ (i,r)\ /\ \partial r \tag{13}$$

where $\partial\ \theta\ (i,r)\ /\ \partial i < 0$ because increased hurricane intensity decreases probability of good health, and $\partial\ \theta\ (i,r)\ /\ \partial r < 0$ because increased residence risk-level decreases perceived probability of good health. Both i and r are therefore positively correlated to ΔEU.

Viscusi (1992) finds that a distinguishing feature of risk research is the way in which the risk variable is created. Most research uses no objective measure of risk. Ideally, the subjective measure of risk can be interacted with an objective measure to produce a more refined measure of risk. Viscusi (1979) linked an objective risk index with a measure of worker's subjective risk perception. He observed the expected positive correlation between the two risk measurements. I use an interaction between the variables for wind and flood risk (subjective risk variables) with the dummy variables for island residence and mobile home (objective risk variables).

IV. Data

RP and SP Methods

Louviere (1996) lays out a framework by which RP and SP data can be combined. He states that the key issue in “rescaling,” as he calls the comparison of utilities estimated from RP and SP data, is whether there exists some logical transformation of SP data from which valid inferences can be made about RP behavior in a manner consistent with economic theory.

Louviere states that RP and SP data are unlikely to have equal variability, but if the choice processes underlying both data sets are similar, then the utility functions should be proportional to each other. RP data are often limited due to strong correlation between variables and limitations in the range of choices. SP data tends to be limited by its hypothetical nature. Combining RP and SP through any number of hypothetical scenarios enables us to control for these limitations. See Whitehead, Haab, and Huang (1999) for an example. They suggest that one limitation of RP approaches involves the limitations of the quality variable, which is analogous to the risk variable problem in this analysis.

The data for this analysis come from a survey of North Carolina residents who were affected by Hurricane Bonnie in the summer of 1998 (Maiola et. al, 1999). This survey used a random digit dialing sample of households in the eight NC coastal counties – Brunswick, Carteret, Currituck, Dare, Hyde, New Hanover, Onslow, and Pender. Respondents were interviewed by phone using a formatted script. Of the households contacted, 76% completed the interview. The original data set had 1029 observations. Observations with missing values were deleted from the sample. The revised data set includes 938 observations. Descriptive statistics for the data are shown in Table 1. The questions used to obtain these variables are presented in Appendix A.

(RP) EVACUATE indicates whether the individual evacuated during Bonnie. (SP) EVACUATE indicates whether they would evacuate if another hurricane were to strike. Appendix B describes the procedure by which the evacuation variables was constructed. Respondents were asked the following SP questions concerning a future hurricane threat with a randomly assigned hurricane category:

> *Please consider the following information...hurricanes are rated on a scale of 1 to 5. Category 1 is a minimal hurricane, 2 is moderate, 3 is extensive, 4 is extreme, and 5 is a catastrophic hurricane. Bonnie was a category 3 (Fran was a 3, Bertha was a 2, and Hugo was a 4). Suppose a category X hurricane is approaching North Carolina. The hurricane has winds greater than Y miles per hour and a storm surge greater than Z feet above normal (Storm surge is the rise in sea level during a hurricane).*
>
> 1. *If a Hurricane Watch is announced, would you evacuate your home to go someplace safer?*
>   (If no then the next question is asked.)
> 2. *If you were given a voluntary evacuation order, would you evacuate your home to go someplace safer?*
>   (If no then the next question is asked.)
> 3. *If you were given a mandatory evacuation order, would you evacuate your home to go someplace safer?*
>   (If no then the next question is asked.)
> 4. *If a Hurricane Warning is announced would you evacuate your home to go someplace safer?*

The variables for X, Y, and Z were different for each storm category X (1,…,5).

In Table 1 descriptive statistics are presented for the two variables that vary between the revealed and SP data - EVACUATE and lnCOST. Of all households in the survey 26% evacuated during Hurricane Bonnie, while 39% stated they would evacuate in the threat of a future hurricane.

lnCOST is the predicted log cost of an evacuation. A summary of evacuation costs is presented in Table 1 as well as the descriptive statistics for lnCOST. Households had an average log cost of evacuation of 3.66 during Hurricane Bonnie and stated that they would spend 3.78 in a hypothetical situation. The total cost of evacuation was estimated using the sum of costs for lodging, food and beverages, automobile, entertainment, and miscellaneous costs. Medical costs and indirect costs due to lost income are ignored so that only the direct costs of the evacuation are considered. For individuals who did not evacuate lnCOST is created using regression based imputation (see Appendix C). The log of total costs is used because of better statistical fit in the imputation procedure.

VEO and MEO indicate whether an individual received a voluntary evacuation order or a mandatory evacuation order during hurricane Bonnie. FLODRISK and WINDRISK are variables used to measure the perceived risk-level of the household's residence, one being the low-risk category, and three being the high-risk variable. EVACPLAN indicates whether or not the household had a recommended "household evacuation plan." NEIGEVAC is a measure of the number of household's neighbors who evacuated. PETS indicates if the household has a pet. MOBLHOME indicates whether or not the family/individual lived in a mobile home at the time that Bonnie struck. ISLAND indicates that the household lived on an island at the time that Bonnie struck. PROPDAMA indicates whether or not the household suffered any property damage. WHITE indicates whether the respondent is white or nonwhite. FEMALE indicates whether the respondent is male or female. WORKFULL indicates whether or not the respondent worked full time at the time that Bonnie struck.

CATEGORY indicates the category of the storm that the respondent faced in the hypothetical scenario. CAT1, CAT2, CAT3, CAT4, and CAT5 are dummy variables.

BRUNCO, CARTCO, CURRCO, DARECO, HYDECO, NEWHCO, ONSLCO, and PENDCO are dummy variables designating the county that the respondent resided in at the time that Bonnie struck.

Table 2 shows the distribution of respondents by the storm category they were presented with under SP. The percentages of respondents who evacuated are reported in the table under the four different scenarios. When asked the SP questions, individuals responded in the expected manner. Those who faced a higher scale of hurricane were more likely to evacuate in all scenarios. Of the individuals who responded to a category one hurricane, 19% stated that they would evacuate under a hurricane watch, 31% given a voluntary evacuation order, 63% given a mandatory evacuation order, and 64% under a hurricane warning.

Of individuals who responded to a category two hurricane, 21% stated that they would evacuate under a hurricane watch, 32% given a voluntary evacuation order, 68% given a mandatory evacuation order, and 69% under a hurricane warning.

Of individuals who responded to a category three hurricane, 28% stated that they would evacuate under a hurricane watch, 41% given a voluntary evacuation order, 76% given a mandatory evacuation order, and 76% under a hurricane warning.

Of individuals who responded to a category four hurricane, 48% stated that they would evacuate under a hurricane watch, 57% given a voluntary evacuation order, 79% given a mandatory evacuation order, and 80% under a hurricane warning.

Of individuals who responded to a category five hurricane, 62% stated that they would evacuate under a hurricane watch, 72% given a voluntary evacuation order, 91% given a mandatory evacuation order, and 92% under a hurricane warning. A mandatory evacuation order seems to maximize the evacuation response. This is suggested by the minimal increase in evacuation response from a mandatory evacuation order to a hurricane warning.

V. Empirical Results

Empirical Model

In order to examine the magnitude and direction of independent variables on the evacuation decision I use a logistic regression model. It is a choice probability model that uses EVACUATE as the dependent variable:

$$\Pr(\text{evac}) = 1/(1+e^{-\beta' X})$$

where X is the set of independent variables and β is the set of coefficients on these variables. A choice of one is an evacuation and a choice of zero is no evacuation. All models are applied to the combined set of RP and SP data with 1,086 observations.

Empirical Results

The RP and SP data are compared in order to test for the consistency of the underlying utility functions. This comparison is made in the first of the following four subsections. The other three logistic models are chosen to represent the household evacuation decision. All three models use demographic variables, hurricane characteristics, income, evacuation cost, a dummy variable for pets, a variable for the number of neighbors who evacuated, and different combinations of risk variables that vary between the models. The risk variables in model 1 are straight risk variables for wind risk, flood risk, island residence, and mobile home residence. Model 2 has the same straight risk variables but also includes interactive risk variables that estimate the weight that different households place on objective risk measurements. Model 3 employs only the interactive risk variables. I use the odd ratios to interpret the effects of the independent variables on the evacuation decision. Odds ratios equal to one represent a 50/50 chance of the household evacuating. For variables with positive coefficients I report the given odds ratio as a ‘more likely to evacuate’ value. For variables with negative coefficients I report a ‘less likely to evacuate’ value using the inverse of the odds ratio (1/odds ratio). All odds ratios are reported as the absolute value.

Comparison of Stated and RP Models

Louviere (1996) suggests testing the SP data to see if valid inferences can be made about RP behavior in a manner consistent with economic theory. To test for differences in the underlying difference in utility functions of the RP and SP data a comparison of evacuation determinants is made (Table 3). Column one is RP response for individuals affected by Hurricane Bonnie, and column two is SP response for all individuals. The coefficient for white individuals becomes significant from RP to SP responses at the 90% confidence level. SP white individuals are 1.53 times less likely to evacuate than all other races. Coefficients for female and education are significant at the 90% confidence level for RP individuals but are insignificant for SP individuals. RP females are 1.43 times more likely to evacuate than males and education level increases likelihood of evacuation by 1.09. Evacuation costs are significant at the .05 level in the RP model so that households are 1.44 times less likely to evacuate with increased evacuation costs. Costs are not significant for SP individuals.

All other variables are consistent between RP and SP response. There are only slight differences in the magnitude of evacuation likelihood except for voluntary evacuation orders and neighbors evacuated. RP individuals are 1.65 times more likely to evacuate under a voluntary order while SP individuals are 2.30 times more likely. RP individuals are 2.47 times more likely to evacuate with an increase in the number of neighbors who evacuated, and SP individuals are 1.3 times more likely.

The differences in the significance between the variables white, female, education, and evacuation costs raises concerns about the consistency between the RP and SP data. These four variables were included as SP interactions (SP*white, SP*female, SP*education, and SP*cost) in the model to test for RP/SP consistency. The SP*cost interaction is the only variable in the model that has a significant effect on evacuations. This implies a 'SP effect' on the cost variable that needs to be controlled for.

Model 1

Model 1 is used to control for the 'SP effect' on costs (Table 4). The coefficient for SP is negative and significant at -0.7950 where before it was positive and significant at 0.382. The coefficient for SP*lnCOST is 0.3192 and significant. Cost of evacuation has a coefficient of –0.158 before SP is controlled for, and a coefficient of –0.343 after. This 'SP effect' suggests there is an underestimation of evacuation costs in individuals' SP and SP*lnCOST should be included.

Model 1 with uses straight risk variables for wind risk, flood risk, island residence, and mobile home residence. Flood risk and mobile home residence are both significantly different from zero at the 95% confidence level. Households with perceived flood risk are 1.6 times more likely to evacuate than those without, increasing with the level of flood risk. Mobile home residents are almost five times more likely to evacuate than other residents. Neither wind risk or island residence is significant. This may be due to a strong correlation between mandatory evacuation orders and island residence and correlation between flood risk and island residence. This would cause most of the households to be captured by the MEO and flood risk variables.

Individuals SP response suggests that they are 2.21 times more likely to evacuate in a future hurricane than they were during Hurricane Bonnie. The total SP effect can be estimated from the results in Table 4:

$$\partial\pi / \partial SP = -0.795 + 0.32 * \ln COST$$

$$= -0.795 + 0.32*(3.7) = 0.389$$

$$\exp(0.389) = 1.48$$

Individuals are 1.48 times more likely to say they will evacuate in the threat of a future hurricane than is observed by their RP behavior.

As evacuation cost increases by 100%, households are 1.41 times less likely to evacuate. A somewhat more realistic increase of 10% will lead an individual to be 1.034 times less likely to evacuate. The coefficient for income is not significantly different from zero. White individuals are more likely to evacuate than all other racial groups. Higher education suggests a slight increase in likelihood of evacuation. Individuals who received a voluntary evacuation order are twice as likely to evacuate than those who did not receive an order at all, while those who received a mandatory evacuation order are almost five times more likely to evacuate.

Households respond in expected ways with storm category. Individuals who faced a category one storm in the hypothetical scenario are 1.72 times less likely to evacuate than those who faced a category three storm. The coefficient for a category two storm is not significant. Individuals who faced a category four or five storm are 2.82 and 7.48 times more likely to evacuate than those who faced a category three storm, respectively. Households with pets are 1.67 times less likely to evacuate than those without. Households who have at least some neighbors who evacuate are 1.75 times more likely to evacuate themselves. Likelihood increases when most or all of them evacuate.

Model 2

Model 2 includes only interactive risk variables (Table 5). This model assumes that the base level of perceived wind or flood risk does not matter. It allows us to see these subjective risks as they vary between mobile home residents and island residents. For example, island residents knows that they live on an island, but must consider for themselves whether or not their home is subject to flood damage during a hurricane strike (FLD_ISLE).

There are four interaction variables between measures of subjective risk (flood risk and wind risk) and objective measures of risk (island and mobile home residence). The interaction between perceived flood risk and island residence (FLD_ISLE) and the interaction between perceived wind risk and mobile home residence (WIN_MOB) are both significant at the 95% confidence level. The interaction between perceived wind risk and island residence (WIN_ISLE) and the interaction between perceived flood risk and mobile home residence (FLD_MOB) are both significant at the 90% confidence level.

Island residents with perceived flood risk are 1.66 times more likely to evacuate with each higher level of perceived flood risk than non-island residents. The coefficient for island residents with perceived wind risk is negative, implying that they are 1.32 times less likely to evacuate with each higher level of perceived wind risk than non-island residents. Mobile home residents with perceived flood risk are 1.51 times more likely to evacuate with each higher level of perceived flood risk than non-island residents. Mobile home residents with perceived wind risk are 1.5 times more likely to evacuate with each higher level of perceived wind risk than non-mobile home residents. All other coefficients have very similar effects in both direction and magnitude as model one.

Model 3

Model 3, presented in Table 6, includes interactive risk variables in addition to the straight risk variables used in model 1. FLODRISK and MOBLHOME are both significant at the 95% confidence level. Households with flood risk are 1.82 times more likely to evacuate. Mobile home residents are 3.66 times more likely to evacuate. Neither ISLAND nor WINDRISK are significantly different from zero. No interactive risk variables are significant.

Selecting a Model

Out of the three models, model 1 with the SP/cost interaction appears to represent the data most accurately. Model two produces significant coefficients for both island interactions but the coefficient for island residents suggests that those individuals are less likely to evacuate with increasing wind risk. The model chi-square is much higher for model one as well (648.6 vs. 619.9). Model three is not used because the subjective risk variables did not differ between objective risk variables (the interactive risk variables were not significant). Coefficients from this model are used in the following equation to produce an index variable (equation 14):

$$\boldsymbol{\beta}'\mathbf{X} = -3.1562 - 0.7950*(SP=0) - .3428*LNCOST + 0.00169*INCOME2 + 0.3192*(SP\_LCOST=0) + 0.2860*FEMALE - 0.3262*WHITE + 0.0700*EDUC + 0.4713*FLODRISK + 0.608*WINDRISK + 1.5915*MOBLHOME + 0.0266*ISLAND + 0.0938*VEO + 1.5651*MEO - 0.5440*CAT1 - 0.3573*CAT2 + 1.0350*CAT4 + 2.0122*CAT5 - 0.5122*PETS + 0.5576*NEIGEVAC$$

The SP and SP_LCOST variables are set to zero in order to remove the ‘SP effect’ from the model. This allows us to make predictions on evacuation costs consistent with observed behavior. The linear form is then converted to a probability using the following equation:

$$\textbf{\textit{Probability of Evacuation}} = 1 / (1 + (\exp(-\boldsymbol{\beta}'\mathbf{X})))$$

The probabilities of evacuation are given in Table 7, where they are presented by storm categories.

VI. Estimating the Costs

Using equation (14) I predicted the probability of evacuation by category for the total population from eight coastal counties (Table 7). Under a category 1 storm, the predicted probability of evacuation is 0.371, for a category 2 storm it is 0.359, for a category 3 storm it is 0.436, for a category 4 storm it is 0.627, and for a category 5 storm it is 0.749.

The population for the eight coastal counties is taken from Maiola, et. al.,(1999). The combined population of the eight NC coastal counties is 514,511. To compute the predicted number of evacuees for each storm category the probability of evacuation is multiplied by the total population. In a category one storm 190,713 are expected to evacuate from the eight NC coastal counties; 184,478 in a category two storm; 224,088 in a category three storm; 322,489 in a category four storm; and 385,260 in a category five storm.

The costs of evacuation can be separated into two components, direct and indirect costs. Direct costs of evacuation are those incurred during the time households are away from home, while indirect costs include the income lost during the evacuation. To compute the direct costs of evacuation, the predicted number of evacuees is multiplied by $112 per household for each category storm (taken form Maiola, et. al., (1999)). Costs for a category one storm are estimated at $21.4 million; $20.7 million for a category two storm; $25.1 million for a category three storm; $36.1 million for a category four storm; and $43.1 million for a category five storm.

To compute the total costs of evacuation, the predicted numbers of evacuees are multiplied by $323 per household for each category storm. Total costs for a category one storm are estimated at $61.6 million; $59.6 million for a category two storm; $72.4 million for a category three storm; $104.2 million for a category four storm; and $124.4 million for a category five storm. These results assume that all individuals are presented with a voluntary and a mandatory evacuation order.

To examine the impact of evacuation orders on the probabilities of evacuation, I set up several different scenarios using different combinations of evacuation orders. The probabilities for different combinations of evacuation orders are presented in Table 8 by category. In a category 1 storm 33% will evacuate with no evacuation order; 35% with a voluntary order; 62% under a mandatory order; and 63% if both voluntary and mandatory orders are given. In a category 2 storm 32% will evacuate with no order; 33% with a voluntary order; 61% with a mandatory order; and 63% if both orders are given. In a category 3 storm 40% will evacuate with no order; 42% with a voluntary order; 69% with a mandatory order; and 71% if both orders are given. In a category 4 storm 60% will evacuate with no order; 62% with a voluntary order; 84% with a mandatory order; and 85% if both orders are given. In a category 5 storm 73% will evacuate with no order; 74% with a voluntary order; 91% with a mandatory order; and 92% if both orders are given.

These probabilities are used to estimate costs of evacuation (shown in Table 9) in the same manner as in Table 7. In a category 1 storm NC's coastal population will spend $19.1 million dollars in direct costs of evacuation and $55.1 million in total costs with no evacuation order; under a voluntary order, $20 million in direct costs and $57.7 million in total costs; under a mandatory order, $35.4 million in direct costs and $102.1 million in total costs; with both evacuation, $36.4 million in direct costs and $105 million in total costs.

In a category 2 storm they will spend $18.3 million dollars in direct costs of evacuation and $52.9 million in total costs with no evacuation order; under a voluntary order, $19.2 million in direct costs and $55.5 million in total costs; under a mandatory order, $35 million in direct costs and $100.9 million in total costs; with both evacuation orders, $36 million in direct costs and $104 million in total costs.

In a category 3 storm they will spend $23 million dollars in direct costs of evacuation and $66.4 million in total costs with no evacuation order; under a voluntary order, $24 million in direct costs and $69.2 million in total costs; under a mandatory order, $39.9 million in direct costs and $115.1 million in total costs; with both evacuation orders, $40.8 million in direct costs and $117.7 million in total costs.

In a category 4 storm they will spend $34.4 million dollars in direct costs of evacuation and $99.2 million in total costs with no evacuation order; under a voluntary order they will spend $35.4 million in direct costs and $102.1 million in total costs; under a mandatory order they will spend $48.5 million in direct costs and $139.8 million in total costs; with both evacuation orders they will spend $49.1 million in direct costs and $141.6 million in total costs.

In a category 5 storm they will spend $41.9 million dollars in direct costs of evacuation and $120.7 million in total costs with no evacuation order; under a voluntary order, $42.7 million in direct costs and $52.6 million in total costs; under a mandatory order, $52.6 million in direct costs and $151.7 million in total costs; with both evacuation orders, $53 million in direct costs and $152.8 million in total costs.

VII. Conclusions

This paper provides further insight towards behavior of households during the threat of a hurricane. I have discussed the thought process through which individuals tend to structure their decisions during situations involving risk. Households have four different utility levels on which they base decisions. I am able to simplify these by making the household's decision a function of health and income.

I have examined different measures of risk and how households tend to interpret and react to them. In this study subjective risk measurements (wind and flood risk) do not vary across objective risk measurements (island and mobile home residence). This implies that individuals are interpreting risk in the same manner wherever they live. Mobile home residence and flood risk perception are consistently significant throughout the analysis. The literature supports the suggestion that household residence is one of the best predictors. This study suggests that an individual's subjective view of risk is the best predictor of evacuation behavior. It is this subjective nature of risk perception that makes risk analysis a very complicated area of study.

Wording and dissemination of evacuation advice and orders is also supported in the literature as a good predictor. In this analysis households tend to respond to hurricane warnings and watches as well as voluntary and mandatory evacuation orders in the expected manner. Household evacuation decisions were also consistent with the severity of the storm.

Other demographic variables including race, sex, and education are significant in the models and give some generalizations to the profile of people who are more likely to evacuate than others. Income shows no significant results in this analysis.

The combined RP data and SP data with different hurricane scenarios is useful for examining the separate effects of different variables on public response. There is a significant 'SP effect' when estimating costs in the hypothetical scenarios. This should be controlled for in order to make predictions on evacuation costs consistent with observed behavior. All other variables appear to contribute similarly between the two data sets.

Inclusion of the cost variable is an asset to the probability model. Evacuation is an economic decision that consumers confront during a hurricane threat and should be treated as such by including a price (cost) variable. The estimated cost of evacuation presented in Table 7 is a measure of the household's response to the information they receive during a hurricane threat and the subjective assessment of the risk they are confronted with. Households appear to react to a category two storm in the same manner as a category one storm. Category three, four, and five hurricanes show significant jumps in the costs due to large increases in the perceived level of risk implied by each category.

The impact of a mandatory evacuation order on costs is very large compared to the impact of a voluntary order. A voluntary order produces minimal increases in evacuation costs above costs produced with no order. These results support the fact that a mandatory order is the only effective policy for producing significant changes in evacuation behavior.

Benefit-Cost Analysis

These results can be an input into further analysis of hurricane evacuation decisions. A Benefit-Cost analysis requires these cost estimates but also requires further analysis of the fatalities caused by hurricanes. Further analysis of fatalities is not covered in this analysis. Using an estimate from the vast literature in value-of-life research we can produce a reasonable estimate of the lives saved by voluntary and mandatory evacuation order for each category of hurricane. I chose a value-of-life estimate from Mrozek and Taylor (1999) who use a meta-analysis approach to produce their results.

They incorporated 23 different value-of-life studies that reported a total of 142 estimates. They conclude that depending on the probability of death that individuals are faced with, value-of-life can be estimated between $1 and $1.3 million dollars.

I assess the efficiency of evacuation orders by comparing the number of statistical lives that would have to be saved by a mandatory evacuation order for benefits to be greater than the costs. This is calculated by taking the difference between the costs of a voluntary order and the costs incurred if both orders are given. I use the direct cost estimates taken from Table 9.

In a category one storm the added direct cost of a mandatory evacuation order is $16.40 million. Using $1 million for the value of a statistical life (VSL), approximately 16 lives would have to be saved by a mandatory evacuation order to justify on efficiency. For a MEO to be efficient it would have to save at least 16 lives.

To justify a mandatory evacuation order in a category two storm 17 lives should be saved. A mandatory evacuation order in a category three storm should save 17 lives as well. In a category four storm 14 lives should be saved by a mandatory evacuation order and in a category five storm 10 lives should be saved.

Hurricane Andrew was a category four hurricane that made U.S. landfall in Florida. In Dade County alone, Andrew resulted in 15 fatalities directly related to the storm and a total of 39, which includes those indirectly related to the hurricane. A mandatory evacuation order would have been cost-effective in this case. Hurricane Bonnie caused 3 total deaths, which were not localized in one area. A mandatory evacuation order to cover the entire area of the hurricane's path would not have been cost-effective.

The VLS reported by Mrozek and Taylor (1999) is towards the lower bound of VLS estimates. The Environmental Protection Agency (EPA) uses a value of $4.8 million that they computed from 26 different studies. Using this value, approximately 3 lives would have to be saved by a mandatory evacuation order to justify on efficiency for a category one storm. To justify a mandatory evacuation order in a category two storm 3 lives should be saved. A mandatory evacuation order in a category three storm should save 4 lives. In a category four storm 3 lives should be saved by a mandatory evacuation order and in a category five storm 2 lives should be saved. The more weight that is placed on a statistical life the less restrictive the conditions are that need to be met to install policy.

Future Research Suggestions

The results from this analysis have given much of the credit for evacuation behavior to the subjective assessment of the individual rather than more objective means, i.e. household residence. What is it that makes a person feel safe or unsafe? These results suggest that basic demographic variables as well as a cost variable should be considered in this type of assessment. If specific attention is given to subjective risk and what factors motivate one's assessment of risk, emergency managers could improve the dissemination of information to the public during a hurricane threat.

What is the additional traffic threat associated with a mandatory order? This should be examined if full cost-benefit analysis is to be made in order to avoid any bias in the estimates. Since additional traffic in the evacuation pathway may cause an additional health risk these benefit estimates may be downward biased. Additional lives should be saved by the evacuation order to account for the additional health risk.

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Figure 1. Path of Hurricane Bonnie and the Distribution of Hurricane Watch and Warning

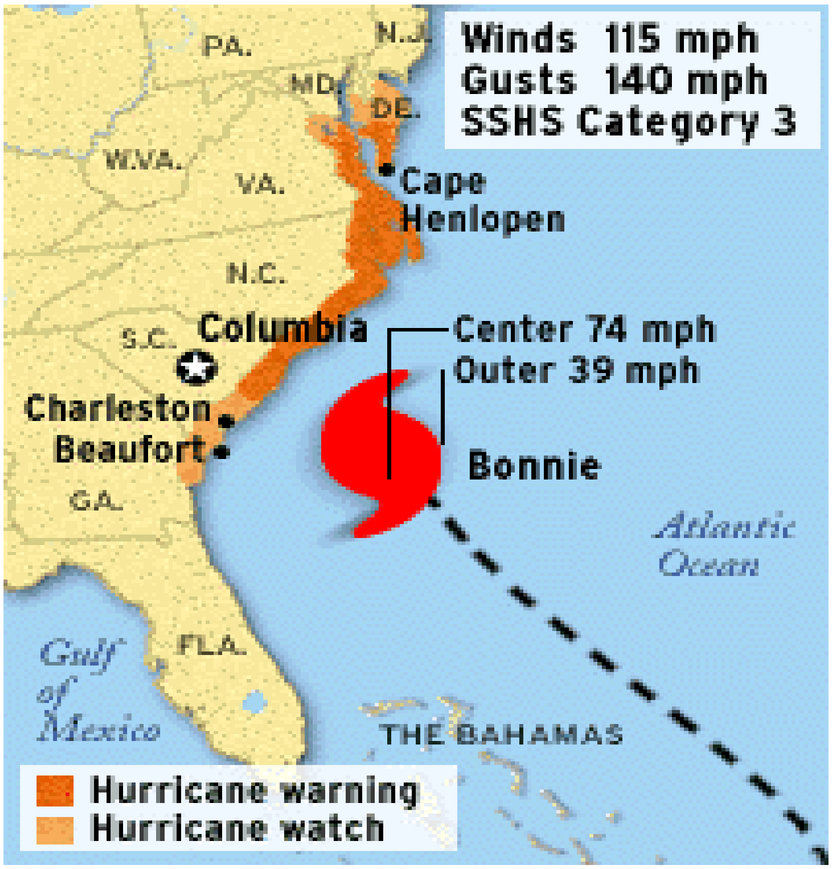
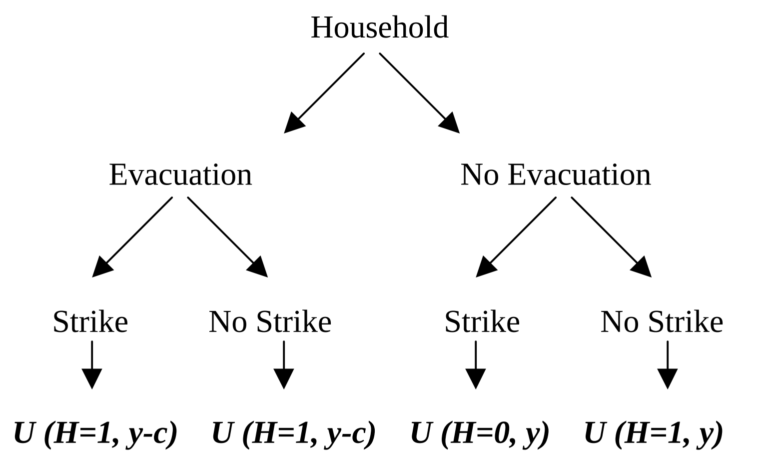


Figure 2. Expected Utility under Complete Uncertainty (Household utilities are represented in parenthesis)



Constructed from Burton et al (1993).

Table 1. Descriptive Statistics for the Data (n=938)

Variable	Mean	Standard Deviation	Minimum	Maximum
VEO	0.16	0.37	0	1
MEO	0.14	0.35	0	1
FLODRISK	1.56	0.72	1	3
WINDRISK	2.15	0.71	1	3
EVACPLAN	0.48	0.50	0	1
NEIGEVAC	1.87	0.90	1	3
PETS	0.66	0.47	0	1
MOBLHOME	0.15	0.36	0	1
ISLAND	0.15	0.35	0	1
PROPDAMA	0.35	0.48	0	1
AGE	46.60	16.60	18	87
EDUC	13.67	2.16	10	18
INCOME2	42.25	30.95	7.50	150
WHITE	0.84	0.37	0	1
FEMALE	0.62	0.49	0	1
WORKFULL	0.53	0.50	0	1
BRUNCO	0.11	0.31	0	1
CARTCO	0.13	0.34	0	1
CURRCO	0.04	0.19	0	1
DARECO	0.05	0.22	0	1
HYDECO	0.03	0.16	0	1
NEWHCO	0.27	0.44	0	1
ONSLCO	0.27	0.45	0	1
PENDCO	0.10	0.30	0	1
(RP)EVACUATE	0.26	0.44	0	1
(SP)EVACUATE	0.39	0.49	0	1
(RP)ln(COST)	3.66	1.01	1.08	8.07
(SP)ln(COST)	3.78	1.15	1.34	9.25
Lodging Costs	$25.19	76.49	0	400
Food &Beverages	$53.10	72.07	0	400
Gas, Oil, & Auto	$24.55	44.57	0	350
Entertainment	$3.65	19.31	0	200
Miscellaneous	$5.58	30.64	0	400

Table 2. SP Evacuation Response Under Different Scenarios

			Evacuation Order		
Scale Category	**Sample Size**	**Hurricane Watch**	**Voluntary**	**Mandatory**	**Hurricane Warning**
1	206	19%	31%	63%	64%
2	217	21%	32%	68%	69%
3	204	28%	41%	76%	76%
4	195	48%	57%	79%	80%
5	187	62%	72%	91%	92%

Table 3. Comparison of Models Between RP and SP Responses

	Hurricane Bonnie,RP (Category=3) (n=938)		SP (All Categories) (n=938)	
Variable	Parameter Estimate	Odds Ratio	Parameter Estimate	Odds Ratio
INTERCPT	-4.192*	.	-3.134*	.
	(0.866)		(0.743)	
ISLAND	0.052	1.053	0.012	1.012
	(0.286)		(0.268)	
MOBLHOME	1.639*	5.149	1.611*	5.006
	(0.249)		(0.243)	
WINDRISK	0.091	1.095	0.038	1.038
	(0.142)		(0.121)	
FLODRISK	0.461*	1.586	0.492*	1.636
	(0.135)		(0.122)	
WHITE	-0.195	1.22	-0.424**	1.529
	(0.262)		(0.226)	
FEMALE	0.355**	1.426	0.257	1.293
	(0.199)		(0.170)	
EDUC	0.084**	1.088	0.059	1.061
	(0.049)		(0.042)	
LNCOST	-0.361*	1.435	-0.015	1.015
	(0.096)		(0.073)	
INCOME2	0.003	1.003	0.001	1.001
	(0.003)		(0.003)	
VEO	0.503*	1.654	0.871*	2.390
	(0.245)		(0.230)	
MEO	1.543*	4.679	1.571*	4.809
	(0.299)		(0.295)	
PETS	-0.575*	1.779	-0.479*	1.616
	(0.205)		(0.180)	
NEIGEVAC	0.902*	2.465	0.261*	1.298
	(0.115)		(0.103)	
CAT1	.	.	-0.554*	1.739
	.	.	(0.262)	
CAT2	.	.	-0.381	1.464
	.	.	(0.260)	
CAT4	.	.	0.999*	2.717
	.	.	(0.250)	
CAT5	.	.	1.878*	6.543
	.	.	(0.258)	
	Model Chi-Square= 328.231		Model Chi-Square= 309.294	

Standard Error in Parenthesis.
* = significant at a 95% confidence level.
** = significant at a 90% confidence level.

Table 4. Logit Model 1 – Controlling for Cost Variation with Straight Risk Variables Only

Variable	Without SP/Cost Interaction			With SP/Cost Interaction		
	Parameter Estimate	Standard Deviation	Odds Ratio	Parameter Estimate	Standard Deviation	Odds Ratio
INTERCEPT	-3.851*	-0.5511	.	-3.1562*	0.6038	.
FLODRISK	0.462*	-0.089	1.587	0.4713*		1.602
WINDRISK	0.066	-0.091	1.068	0.0608	0.0917	1.063
MOBLHOME	1.599*	-0.172	4.946	1.5915*	0.172	4.911
ISLAND	0.00417	-0.193	1.004	0.0266	0.1949	1.027
SP	0.382**	-0.202	1.466	-0.795**	0.4652	2.21
LNCOST	-0.158*	-0.057	1.171	-0.3428*	0.089	1.41
INCOME2	0.002	-0.0023	1.002	0.00169	0.00226	1.002
WHITE	-0.317**	-0.168	1.374	-0.3262**	0.1689	1.39
FEMALE	0.289*	-0.128	1.335	0.286*	0.1283	1.331
EDUC	0.072*	-0.0318	1.074	0.07*	0.0319	1.073
VEO	0.695*	-0.1647	2.003	0.6938*	0.1658	2.001
MEO	1.554*	-0.2069	4.73	1.5652*	0.2086	4.784
PETS	-0.511*	-0.134	1.667	-0.5122*	0.1341	1.67
NEIGEVAC	0.563*	-0.0751	1.755	0.5576*	0.0754	1.747
CAT1	-0.592*	-0.268	1.808	-0.544*	0.2685	1.72
CAT2	-0.391	-0.267	1.479	-0.3573	0.2663	1.43
CAT4	1.015*	-0.254	2.758	1.035*	0.2539	2.815
CAT5	2.049*	-0.261	7.762	2.0122*	0.261	7.48
SP_LCOST				0.3192*	0.114	1.376
Model Chi-square =	640.587			648.575		

Data includes RP and SP response.
* = significant at a 95% confidence level.
** = significant at a 90% confidence level.

Table 5. Logit Model 2 with Interactive Risk Variables Only

Variable	Parameter Estimate	Odds Ratio
INTERCPT	-2.926*	.
	(0.516)	
FLD_ISLE	0.509*	1.664
	(0.181)	
WIN_ISLE	-0.280**	1.321
	(0.153)	
FLD_MOB	0.410**	1.506
	(0.219)	
WIN_MOB	0.408*	1.503
	(0.158)	
SP	0.415*	1.514
	(0.201)	
LNCOST	-0.163*	1.176
	(0.057)	
INCOME2	0.002	1.002
	(0.002)	
WHITE	-0.383*	1.466
	(0.167)	
FEMALE	0.307*	1.359
	(0.127)	
EDUC	0.067*	1.069
	(0.031)	
VEO	0.709*	2.033
	(0.164)	
MEO	1.539*	4.659
	(0.203)	
PETS	-0.477*	1.613
	(0.132)	
NEIGEVAC	0.589*	1.801
	(0.075)	
CAT1	-0.65*	1.916
	(0.269)	
CAT2	-0.435	1.546
	(0.265)	
CAT4	0.951*	2.588
	(0.250)	
CAT5	1.956*	7.067
	(0.258)	
Model Chi-square = 619.934		

Data includes RP and SP response.
Standard Error in Parenthesis.
* = significant at a 95% confidence level.
** = significant at a 90% confidence level.

Table 6. Logit Model 3 with Straight and Interactive Risk Variables

Variable	Parameter Estimate	Odds Ratio	Variable	Parameter Estimate	Odds Ratio
INTERCPT	-3.637*	.	MOBLHOME	1.299*	3.664
	(0.568)			(0.532)	
WHITE	-0.319**	1.376	FLD_ISLE	0.228	1.256
	(0.168)			(0.216)	
FEMALE	0.291*	1.337	WIN_ISLE	0.156	1.169
	(0.128)			(0.250)	
EDUC	0.071*	1.074	FLD_MOB	-0.103	1.109
	(0.032)			(0.252)	
SP	0.388**	1.474	WIN_MOB	0.215	1.239
	(0.202)			(0.234)	
LNCOST	-0.158*	1.171	CAT1	-0.608*	1.835
	(0.057)			(0.270)	
INCOME2	0.002	1.002	CAT2	-0.401	1.493
	(0.002)			(0.267)	
VEO	0.707*	2.028	CAT4	1.011*	2.749
	(0.166)			(0.253)	
MEO	1.570*	4.807	CAT5	2.034*	7.645
	(0.208)			(0.261)	
FLODRISK	0.420*	1.818	PETS	-0.505*	1.656
	(0.112)			(0.134)	
WINDRISK	-0.001	1.001	NEIGEVAC	0.557*	1.745
	(0.112)			(0.076)	
ISLAND	-0.77	2.160			
	(0.606)				
Model chi-square = 643.689					

Data includes RP and SP response.
Standard Error in Parenthesis.
* = significant at a 95% confidence level.
** = significant at a 90% confidence level.

Table 7. Estimated Costs of Evacuation for NC's Coastal Population

Storm Category	Number of Survey Respondents	Probability of Evacuation	Total Population of Eight Coastal Counties	Evacuation Cost per Household for NC Coastal Area	
			514,511	Direct Costs	Total Costs
				$112	$323
			Predicted Number of Evacuees	Predicted Evacuation Cost for Total Population	
Category 1	195	0.371 (0.271)	190,713	$21.4	$61.6
Category 2	203	0.359 (0.276)	184,478	$20.7	$59.6
Category 3	1128	0.436 (0.268)	224,088	$25.1	$72.4
Category 4	179	0.627 (0.246)	322,489	$36.1	$104.2
Category 5	171	0.749 (0.189)	385,260	$43.1	$124.4

Predicted costs of evacuation are presented in millions.
Standard Error in parenthesis.
Population and per Household cost is taken from Maiola (1999).

Table 8. Probabilities of Evacuation Using Different Combinations of Evacuation Order

Storm Category	Probability of Evacuation Under Different Combinations of Evacuation Order			
	No Evacuation Orders	Voluntary Order, No Mandatory Order	Mandatory Order, No Voluntary Order	Voluntary Order and Mandatory Order
Category 1	0.332	0.347	0.615	0.632
	(0.243)	(0.246)	(0.233)	(0.229)
Category 2	0.318	0.334	0.607	0.625
	(0.231)	(0.234)	(0.223)	(0.219)
Category 3	0.399	0.417	0.692	0.708
	(0.240)	(0.241)	(0.200)	(0.194)
Category 4	0.597	0.615	0.841	0.852
	(0.235)	(0.231)	(0.135)	(0.128)
Category 5	0.726	0.742	0.913	0.919
	(0.183)	(0.177)	(0.082)	(0.077)

Standard Deviation in parenthesis.

Table 9. Cost Estimates by Hurricane Category and Evacuation Order Scenario

Total Population of Eight Coastal Counties	= 514,511	
Evacuation Cost per Household for NC Coastal Area	Direct Costs =	$112
	Total Costs =	$323

Storm Category	No Evacuation Orders			VEO, No MEO			MEO, No VEO			VEO and MEO		
	# Evacuated	Costs of Evacuation		# Evacuated	Costs of Evacuation		# Evacuated	Costs of Evacuation		# Evacuated	Costs of Evacuation	
		Direct	Total		Direct	Total		Direct	Total		Direct	Total
Category 1	170,640	$19.11	$55.12	178,590	$20.00	$57.68	316,194	$35.41	$102.13	324,969	$36.40	$104.96
Category 2	163,788	$18.34	$55.90	171,801	$19.24	$55.49	312,489	$35.00	$100.93	321,555	$36.01	$104
Category 3	205,432	$23.01	$66.35	214,295	$24.00	$69.22	356,267	$39.90	$115.10	364,515	$40.83	$117.74
Category 4	307,257	$34.41	$99.24	316,175	$35.41	$102.12	432,883	$48.48	$139.82	438,319	$49.09	$141.58
Category 5	373,761	$41.86	$120.72	381,632	$42.74	$123.27	469,533	$52.59	$151.66	472,943	$52.97	$152.76

Cost Estimates presented in millions.

Appendix A: Survey Questions

The following questions were included in the household survey for individuals affected by Hurricane Bonnie. These questions were used to form the variables used in this analysis and were not necessarily presented in this order.

1. What is your gender?

2. What is your race or ethnic background?

3. How old are you?

4. Do you have any pets?

5. How much education have you completed?

6. Are you married?

7. Given a list of income categories respondents were asked to report their total household income.

8. What county do you live in? [BRUNSWICK, CARTERET, CURRITUCK, DARE, HYDE, NEW HANOVER, ONSLOW, OR PENDER, CONCLUDE THIS SURVEY]

9. Which of the following best describes the place you were living at the time of the hurricane...a house, an apartment or townhouse, a mobile home, boat, recreational vehicle, or something else?

10. During this past August, were you working full-time, part-time, in the military, going to school, keeping house, retired, or what?

11. Did an evacuation order cover your home (were you told to leave your home by emergency management officials?)?

12. Was this a voluntary or mandatory evacuation order?

13. Did all, most, some, or none of your neighbors evacuate?

14. Did you evacuate your home to go someplace safer before Hurricane Bonnie hit?

15. Was your hurricane evacuation route planned or unplanned by your household?

16. Did you suffer any property damage to the place you were living from Hurricane Bonnie?

17. Was your home on a barrier island?

18. Was your home on an island?

19. Now consider the risks from wind damage from a hurricane. In your opinion, was the home here you lived at the time of Hurricane Bonnie located in a high-risk site, a medium-risk site, or a low-risk site?

20. Consider the risks from coastal flooding from a hurricane. In your opinion, was the home where you lived at the time of Hurricane Bonnie located in a high-risk site, a medium-risk site, or a low-risk site?

Appendix B: Procedure Used to Produce the Employed Data Set

Three key changes were made to the original data set for this analysis.

1. Observations with missing values for variables containing crucial information were deleted from the sample.

2. A single "evacuation" dummy variable constructed all of the respondent's stated evacuation decisions into one.

3. The RP and SP data were combined into one data set containing 1,876 observations and 34 variables.

Deleting Observations

If any of the following variables had missing values then the observation was deleted from the sample: NEIGEVAC, FLODRISK, AGE, EDUC, and MARRIED. These were considered crucial variables and missing values would affect the quality of the data.

Constructing the "Evacuation" Variable

The evacuation variables were combined to form a single "*yes or no*" response by the household to evacuate in the hypothetical scenario. Respondents experienced one of three scenarios during Hurricane Bonnie – a hurricane watch, a voluntary evacuation order, or a mandatory evacuation order. This information was considered in the SP scenarios by matching the Bonnie experience with the SP questions. This was done in the following manor:

a) If an individual experienced a hurricane watch with no evacuation orders then their response to the first SP question - "*yes or no*" - was accepted and all further scenario responses were discarded.

b) If an individual experienced a voluntary evacuation order during Bonnie then a "*yes*" response for the first question would be accepted, and a "*no*" would be dependent on the second question. A response of “*yes or no*” would be accepted from the second question. All further scenario responses were then discarded.

c) If an individual experienced a mandatory evacuation order during Bonnie then a “*yes*” response for the first question would be accepted, and a “*no*” would be directed to the second question. A “*yes*” response for the second question would be accepted and a “no” response would be dependent on the third question. A response of “*yes or no*” would be accepted from the third question. All further scenario responses were then discarded.

Appendix C: Imputation Procedure for Predicted Log of Evacuation Costs

lnCOST is regressed on the following expected determinants of costs using RP individuals who evacuated during Hurricane Bonnie: RTDIST (round trip distance), HOTEL (dummy variable for staying in a hotel, SHELTER (dummy variable for staying at a public shelter), DAYSGON2 (how many days gone) AGE, BARRISLD (dummy variable for living on a barrier island), and OTHRISLD (dummy variable for living on any other type of island). The coefficients from the regression are presented in the following table.

Coefficients Used for LNCOST imputation

Variable	Parameter Estimate	Standard Error	p-value
INTERCEP	3.139502	0.43196	0.0001
RTDIST	0.003049	0.00048	0.0001
HOTEL	2.111347	0.30091	0.0001
SHELTER	1.033547	0.48532	0.0342
DAYSGON2	0.148442	0.07678	0.0544
AGE	-0.029863	0.00663	0.0001
BARRISLD	0.536148	0.27331	0.051
OTHRISLD	0.817251	0.46465	0.0799

The variable lnCOST is then constructed for ***RP*** from the following equation (A):

$$\boldsymbol{lnCOST} = 3.139502 + \text{RTDIST}(0.003049) + \text{HOTEL}(2.111347) + \text{SHELTER}(1.033547) + \text{DAYSGON2}(0.148442) + \text{AGE}(-0.029863) + \text{BARRISLD}(0.536148) + \text{OTHRISLD}(0.817251)$$

For missing values the following variables were substituted into equation A:

- SPHOTEL (individual stated that they would stay in a hotel during a future evacuation) for HOTEL.
- SPSHELTR (individual stated that they would stay in a shelter during a future evacuation) for SHELTER.

For any other missing values the following were substituted into equation A:

- 0.236 (mean SPHOTEL) for HOTEL.
- 0.122 (mean SPSHELTR) for SHELTER.

lnCOST is then constructed for ***SP*** cases using the following equation where SPRTDIST is the round trip distance an individual stated they would travel during a future evacuation the equation (B):

lnCOST = 3.139502 + SPRTDIST(0.003049) + SPHOTEL(2.111347) + SPSHELTR(1.033547) + DAYSGON2(0.148442) + AGE(-0.029863) + BARRISLD(0.536148) + OTHRISLD(0.817251)

For missing values, a predicted round trip distance variable was constructed to take the place of SPRTDIST. This was done using the following equation(C), with coefficients taken from linear regression:

PREDDIST = -14.59 + RTDIST(0.89) + CATEGORY(26.97)

If there are missing values for PREDDIST then the following was substituted into equation C:

- 177.66 (mean RTDIST) for RTDIST.

For other deleted values of lnCOST, the following were substituted into equation B:

- 0.236 (mean SPHOTEL) for SPHOTEL.
- 0.122 (mean SPSHELTR) for SPSHELTR.

If there are still deleted values for lnCOST then, ***SP*** lnCOST is set equal to ***RP*** lnCOST.